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PRESIDENTIAL TWEETS AND STOCK MARKET: THE BREXIT CASE

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Abstract

Can presidential tweets influence the stock market? The paper answers this question by analyzing Brexit-related tweets posted by Boris Johnson during his premiership. The uninformative nature of Johnson's digital statements suggests that our hypothesis, if confirmed, would contradict the efficient market hypothesis (EMH). Through an event study, we found a positive and statistically significant effect of tweets on the FTSE100's returns. Findings were additionally corroborated by a regression analysis and a robustness check. The positive effect can be attributed to the investors valuing positively the reduced uncertainty on Brexit, but the overreaction to uninformative information remains incompatible with the EMH.

Keywords: Brexit, Twitter, Efficient Market Hypothesis, Asset pricing

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1. Introduction

If there is something more volatile and uncertain than stock markets, that is (probably) the behavior of a politician. Making the (“strong”) assumption that politicians are coherent with what they say, it is possible to grasp useful insights from their public declarations and form expectations about the future actions of a government. Joking aside, there is an important truth: the words pronounced by political leaders have a high specific weight.

Concretely, they can have a dramatic impact on the economic system (consumers’ confidence, investments, job market) and the financial system (stock and bond markets, banking system) within and outside the national boundaries.

Nowadays, social media platforms have created a new, fast and effective written way to communicate. Shrewd politicians have embraced these new media, using direct, more frequent and, sometimes, colloquial contact with people. Moreover, this type of communication has been legitimized. That is, it is used for official and institutional communications.

In the context of the efficient market hypothesis, it is interesting to investigate whether presidential remarks on social media represent an additional (and robust) source of information for investors. According to the efficient market hypothesis (hereinafter EMH), stock prices fully reflect all the information available to investors (Fama, 1969). Depending on what we mean by “available information”, we can distinguish among three forms of the EMH: weak, semi-strong and strong.

The purpose of my research is to challenge the semi-strong market hypothesis, which posits that prices reflect all publicly available information. Whenever new public information is released, rational arbitrageurs (expert traders) compete in order to exploit a temporary market inefficiency and make a profit. Competition is pivotal in order to maintain an equilibrium status. However, there exist some uninformed investors (noise traders) who believe to make a profit even if the information has already been released, either completely or partially.

The statistical significance of (uninformative) social media declarations in determining the market fluctuations, if confirmed, might demonstrate a market inefficiency. Indeed, efficient markets should not be influenced by those types of information.

In order to test the EMH, it was studied the effects of Brexit-related tweets of Boris Johnson, the UK Prime Minister, on the FTSE100 index.

The organization of the paper is as follows. Section 2 briefly introduces the most relevant finance literature related to the topics under discussion. In section 3 are presented the data and the methodology applied to address our research question. Section 4 is the core part of the paper: here are disclosed and discussed the results of the analysis. Section 5 summarises the major findings, their implications and offers insights for future research.

2. Literature review

2.1 Efficient Market Hypothesis

The revolutionary consequence of the EMH is that stock prices move according to a random walk. A random walk is defined as “a simple model where the current value of a series is simply the previous value perturbed by a white noise (error) term” (Brooks, 2014).

Randomness, thus unpredictability, is not inconsistent with efficient prices (i.e. prices fully reflecting available information) as initially hypothesized by scholars (Kendall, 1953). The concept of random movement is strictly associated with new information release, which are indeed unforeseeable, and not to irrational forces driving the markets. In semi-strong efficient markets, it follows that technical analysis, fundamental analysis and active investment strategies are unreliable. However, academia found out a list of market anomalies which challenge the semi-strong hypothesis. Examples of market anomalies include small-firm effect, January effect, neglected stocks, book-to-market ratios. In all these instances, the returns seem to be inconsistent (and higher) with respect to the risk-adjusted returns predicted by a model (CAPM).

2.2 Social Media and Asset Pricing

The proposed paper belongs also to the literature dedicated to the role of information transition in financial markets. As aforementioned, information has a determining role for demand-supply dynamics in stock markets. Accordingly, numerous researches emphasize the media's effects on stocks by differentiating information on the type (numeric or nonnumeric) and the channel of casting (television, newspapers, internet) (Tetlock, 2014). Recently, a niche branch of research devoted to the relationship between social media's information and asset pricing. Contrarily to traditional media, social media lets its users participate both passively and actively in the information transition and allows interactions among users.

A benchmark paper from Chen et. al (2014) demonstrated the existence of a "wisdom of crowds" by conducting a textual analysis on user-articles published on *SeekingAlpha.com,* a leading US social networking site for investors. In practice, the peer opinions shared on the social media significantly foretold future stock returns and earnings surprises.

In general, previous literature focuses chiefly on the effects of tweets (Twitter's posts) on US financial markets. Whether there are obvious reasons behind the rationale of analysing the US financial markets (high liquidity, efficiency, volumes traded), this might not be as clear regarding the choice of Twitter.

There are two main reasons which explain the use of Twitter as the main source of data. First, Twitter allows users to easily get access to voluntarily public shared information through its APIs (application programming interfaces). Whilst there are some constraints on the amount of downloadable data, they are less than the ones imposed by other platforms (for instance Facebook). Second, there exist several software libraries which can access the Twitter API and can be used for data mining.

H. K. Sul et. al (2016) showed how a sentiment analysis on tweets citing a specific stock is linked to the stock returns in the following days. Moreover, the study divided the tweets according to the number of followers of the typing users. Tweets from less followed users and with no retweets, hence not widespread, revealed a more powerful impact on future returns than more followed tweets. Bartov et. al (2018) conducted a similar study, but instead of focusing on stock returns, they tried to test the predictive power of tweets' sentiment analysis on a company's future earnings. Also, in this case, there is a stronger significance for firms in weaker information environments (small size, low analysts' attention, low institutional ownership).

Despite public opinion accent political tweets and common sense would suggest that stock markets might react to those news, there are no renown empirical researches clarifying this issue. This paper attempts to fill this gap and deepen the previous literature by adding two fundamental elements. First, it investigates a new market (FTSE100) based on specific tweets by the UK Prime Minister. Second, in lieu of modelling the research after a tweets' sentiment analysis, the study classifies the announcements according their content (i.e. keywords).

3. Data and methods

3.1 Data

The entire study is built around the Twitter's activity of Boris Johnson. Amidst the thousands of posts from the UK Prime Minister, it was selected a smaller sample of Brexit's tweets written from the beginning of his premiership (24/07/2019) until the most recent Brexit-related tweet (03/02/2020)[1]. With "Brexit's tweets" we mean statements explicitly referring to Brexit. In order to be categorized as such, they needed to contain specific words which are connected to the withdrawal of the UK from the EU. The list of words was created ad hoc for the purpose of the paper and is showcased in *Table 1*. Observations, that is tweets and FTSE100 prices, are on a daily basis.

The constraints applied enable to isolate the announcements made by Boris Johnson, one of the Brexit's strongest supporters, whose government's main purpose was to guide the country to "get Brexit done". Theoretically, rational investors should have been highly confident that Britain would leave the EU under the Johnson's presidency. In an EMH setting, due to the climate of reduced uncertainty and the uninformative content[2] of the public tweets, we would expect the market (FTSE100) to not react to these digital bulletins.

[1] Last update on 26/03/2020.
[2] See *Table 1* in "Annex: Brexit-related tweets".
From a qualitative analysis, it emerges that Johnson does not use his Twitter accounts for official declarations on Brexit. His tweets contain principally political slogans (repeated several times) which do not provide useful insights to investors.

3.2 Event Study

By definition, an event study quantifies the impact of a certain event on a security's value. This procedure has been extensively applied to study the effect on stock prices of events like stock splits, dividend payments, earning announcements, M&A transactions, changes in capital structure. It therefore seems the most appropriate tool to test whether the UK stock market behaved differently after presidential tweets on Brexit.

A schematic approach to event study was presented by MacKinley (1997) and can be summarized through the following 3-stage procedure:

1. Specify the event of interest and the event timeline.
2. Determine a model for the normal stock return and calculate abnormal returns.
3. Build a hypothesis testing on the aggregated abnormal returns.

In the matter in question, the events analyzed are Brexit-related tweets. *Figure 1* shows the timeline of our event study.

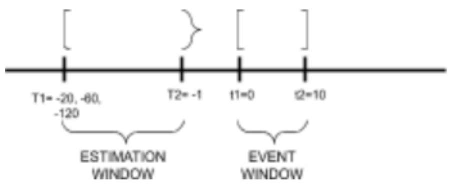

Figure 1

The date in which a tweet is published is identified as the "event date" (*t1*). Each event date is associated with a trading date or an adjusted (trading) date if the tweet is posted on either a non-trading day or at market closed[3]. The adjusted date is simply the next closest trading day.

[3] After 4:30 pm on a trading day.

The event window, namely the period in which the event is studied, goes from the event date (*t1=0*) until the subsequent 10 days (*t2=10*). To investigate short-run effects, it is common to analyze the event date and the 10 days before and after it, in order to have a more comprehensive and accurate view of the phenomenon under consideration (Brooks, 2014). However, in this study, it does not make sense to include days prior to the event date, given that the market cannot acquire in advance the information contained in the tweet.

The estimation window is a period prior to the event date that is used for the computation of the normal returns (i.e. expected returns of the security if the event did not occur). Robustness of results was enhanced by considering three different estimation windows: 1 month (20 days), 3 months (60 days) and 6 months (120 days). It is remarkable to outline that event dates are excluded from the estimation windows to assure the accuracy of normal returns.

The most relevant output in the second step is the calculation of the abnormal returns (*ARs*). The abnormal return of security *i* at time *t* is:

$$AR_{i,t} = R_{i,t} - NR_{i,t} \tag{1}$$

where $R_{i,t}$ is the ex post (actual) returns of the security and $NR_{i,t}$is the normal returns of the security over the estimation window.

Previous literature describes two different approaches for calculating the normal returns: the *constant mean return model* and the *market model*. The former employs the return of a market index in order to capture marketwide price movements, while the latter models a statistical linear relation between the return of the security and the market portfolio (deJong, 2010).

Since the research does not examine a single security or a portfolio of securities, but rather the overall market returns, it makes sense to use the constant mean return model. Indeed, the market model would imply regressing the FTSE100 returns on themselves.

According the constant mean return model, the normal returns are defined as:

$$NR_{i,t} = \frac{1}{T} \sum_{s=T1}^{T2} R_{i,s} \tag{2}$$

where *T=T2-T1+1* is the length of the estimation period and $R_{i,s}$ is the logarithmic return of the FTSE100 at *s*.

With day level observations[4], we derived a sample of *N*=149 events. The abnormal returns on *N* events over the event window can be presented in a matrix notation as follows:

$$\begin{pmatrix} AR_{\mathrm{i,\ t}} & \cdots & AR_{\mathrm{i,\ t+10}} \\ \vdots & \ddots & \vdots \\ AR_{\mathrm{N,\ t}} & \cdots & AR_{\mathrm{N,\ t+10}} \end{pmatrix}$$

Inferences can be drawn by aggregating the *ARs* in 2 modes: through time for the same event, through time and across events.

The time aggregation is done through the average of abnormal returns (*AAR*) at time t ($t1 \leq t \leq t2$):

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,t} \tag{3}$$

The *AAR* isolates the effects related to the event because the average value neutralizes all possible noisy information (unrelated to the event).

The second type of aggregation is accomplished by averaging the cumulative abnormal returns (*CARs*). *CARs* assort abnormal returns by event and can help to examine the returns over the entire event window:

[4] A single abnormal return is calculated for each event date, no matter how many tweets were made in the same day.

$$CAR_i = \sum_{t=t1}^{t2} AR_{i,t} \tag{4}$$

As before, inferences are computed on an average value, namely the cumulative average abnormal return (*CAAR*):

$$CAAR \quad = \frac{1}{N} \sum_{i=1}^{N} CAR_i \tag{5}$$

Alternatively, the *CAAR* can be calculated as:

$$CAAR \quad = \sum_{t=t1}^{t2} AAR_t \tag{6}$$

At this point, it is possible to perform a hypothesis testing on the aggregated abnormal returns in order to verify whether they were statistically different from zero. Tests were executed on both *AARs* and the *CAAR*. Hereunder are exhibited the null (H_0) and alternative hypotheses (H_1) of the different tests.

Given an estimation period (*T*), it was tested the *AARs* for each *t* in the event window:

$$H_0: E(AAR_t) = 0$$

$$H_1: E(AAR_t) \neq 0$$

Moreover, for each *T*, we tested:

$$H_0: E(CAAR) = 0$$

$$H_1: E(CAAR) \neq 0$$

A simple t-test was used in order to reject or not H_0. The final decision was set on test statistics (TS) which can be assumed to be normally distributed. The Central Limit Theorem states that in large samples (usually T>30) TS converges to a standard normal distribution:

$$TS_{AAR_t} = \sqrt{N}\frac{E(AAR_t)}{s_{AAR_t}} \approx N(0, 1)$$

$$TS_{CAAR} \quad = \sqrt{N}\frac{E(CAAR)}{s_{CAAR_t}} \approx N(0, 1)$$

where N is the sample size, $E(AAR_t)$ is the sample mean of the *AR* at time *t*, $s_{AAR_t}$is the standard error of AAR_t, $E(CAAR)$ is the estimated *CAAR* and $s_{CAAR_t}$is its standard error. This condition enables us to use the critical values of the cumulative standard normal distribution as a benchmark when testing hypotheses.

3.3 Regression Analysis

A regression analysis was designed to corroborate the results of the event study and to establish a linear relation among the variables of interest. The econometric model adopted is an OLS regression model which comprises daily observations *j* from 24/07/2019 to 03/02/2020.

Models were developed after controlling for issues (non-stationarity, heteroskedasticity and autocorrelation) which could have biased the inferences. The outputs of the econometric tests (ADF, White and Breusch-Godfrey) are disclosed in *Table 2*. It can be noticed that there were no problems of non-stationarity. On the other hand, when necessary, autocorrelation and heteroskedasticity were corrected by using HAC standard errors.

The estimated model has the form:

$$CAR_j = \alpha + \beta_1 log(1 + BJ_j) + \beta_2 CAR_{j-10} + \beta_3 MacroNews_j + \varepsilon_t \tag{7}$$

The independent variable, CAR_j, is the cumulative abnormal return of the FTSE100 at time *j*. The chosen regressors are: BJ_j (a count variable which reflects the number of tweets posted on *j*)[5] , CAR_{j-10} (the CAR of the FTSE100 at time *j-10*) and $MacroNews_j$ (a dummy variable which takes value 1 if there is an interest rates announcement by the BoE on *j* and 0 otherwise).

The presence of CAR as dependent variable and its 10 days lag as independent variable is taken from Chen et al. (2014). Note that CAR_{j-10} is included in order to control eventual effects unleashed by past information (other than tweets), while $MacroNews_j$ ensures that the effects of a critical macroeconomic news is caught. The statistical significance of $\beta_1$would affirm the role of tweets in determining the cumulative market movements over the estimation window.

3.4 Robustness check

The integrity of previous findings was additionally challenged by excluding from our event study days in conjunction with the major events on the Brexit timeline[6] (elections, public statements by influential politicians, relevant parliament sessions at national and European level) and announcements on the base rate by the Bank of England (BoE).

By doing so, we obtained a subsample potentially less biased by alternative sources of information other than Twitter. *Table 3* shows further details on the dates.

The final subsample for the event study has 79 observations, 70 less than the original sample, but still a size large enough to assume a normal distribution of returns. The statistical significance of abnormal returns under the new conditions, if confirmed, would prove the

[5] The logarithmic transformation was applied in order to correct the skewness.
[6] These events are disclosed in “Brexit timeline: events leading to the UK’s exit from the European Union”, a periodic publication available on the House of Commons website.

robustness of the event study. Similarly, we applied the regression analysis (*Equation 7*) to the restricted subsample.

4. Results

4.1 Event Study, regression analysis and robustness check

The outcomes of the event study are at odds with the semi-strong market hypothesis. In essence, the hypotheses testing substantiate that the *CAARs* are statistically different from 0. As exemplified in *Table 4a*, there is statistical evidence of the FTSE100 reacting positively to the Brexit-related tweets of Boris Johnson in the period comprising the event date and the subsequent 10 days. The magnitude of the *CAARs* and the statistical significance of the test is inversely linked to the estimation window's length. Assuming that the market would have behaved as last month, namely considering a 20 days estimation window for normal returns, the estimated cumulative abnormal returns after a Brexit-tweet is 2.64% and it is statistically significant at 1% ($TS_{CAAR_{20\,days}} = 9.78$). With a 3 months estimation window (60 days), the CAAR is 0.69% and is statistically significant at 1%. Finally, results are also confirmed with a 120 days estimation window: CAAR is 0.50% and has a t-stat of 2.12 (significant at 5%).

Hypothesis tests on *ARs* did not prove to be as powerful as the one with *CAARs*. From *Table 4b*, it is evident that *ARs* have a positive sign, but their statistical significance is confirmed only with the shortest estimation window.

As displayed in *Table 5*, the regression models bear coherent results. Overall, the three models show a conspicuous goodness of fit (r^2) which improves as T decreases.

The independent variable which takes into account the tweets, BJ_j, is statistically significant at 1% in all the three models. The coefficient estimates for $log(1 + BJ_j)$ increase as the estimation window shrinks: it varies from 0.0301 (T=120) to 0.0462 (T=20). While the precise coefficient interpretation is not straightforward[7], it is interesting to observe that a higher number of Brexit-related tweets produces a positive effect on the *CARs*.

In accordance with macroeconomic theory (Blanchard, 2017), the outputs disclose the statistical significance of $MacroNews_j$ at 5%: the interest rate announcements by the BoE do influence the market movements. However, the negative sign of the regression coefficient is misleading given that the BoE did not change its base rate in the short period analyzed. Practically, as T=20, the regression coefficient $MacroNews_j$ is -0.0279: CAR_j decreases of 0.0279 each time the BoE made its base rate announcements.

The regression coefficients of CAR_{j-10}, which control for past market trends, are not statistically significant at 5%: we can claim that they have no impact on CAR_j.

Lastly, the robustness check corroborates the previous findings. The more stringent conditions applied to the subsample, aimed at cancelling impacts of (noisy) information other than tweets, validate the positive and statistically significant *CAARs* found in the event study (*Table 6a*). Moreover, the *CAARs* appear remarkably higher and more significant for estimation windows of 60 and 120 days.

As regards the regression analysis, the constraints applied to the subsample did not alter the validity of previous results: figures confirm the statistical significance of BJ_j (*Table 6b*).

[7] For T=20, a 1% increase in *log(1+BJj)* is associated with a 0.000462 unit increase in *CARj*.

4.2 Discussion of results

At a glance, the FTSE100's euphoria after these announcements might seem counterintuitive. Here two questions arise: why should the market react to these uninformative statements and why the reaction is positive?

In our context, it could have happened that uninformed investors either traded impulsively or priced the higher likelihood of Brexit to happen under the Johnson's premiership or simply tried to speculate. Although it is not possible to delineate the exact circumstances that sparked the abnormal returns, it is important to stress the common denominator of the proposed conjectures: the market's reaction to uninformative statements. The latter alone is sufficient to claim that the market failed to comply with the EMH on this occasion.

Literature on information transmission embodies accredited papers which highlighted market overreaction to uninformative media contents and how this phenomenon can help to explain market anomalies (Tetlock, 2014). This does not entail that informative news are irrelevant in asset pricing, but rather that investors do not always react immediately and rationally to information release as the EMH postulates. As suggested by Peng and Xiong (2006), investors tend to emphasize widely applicable and general (market, industry-level) news, which are cheaper to process than detailed, firm-specific information (cash-flows, accruals etc.). It follows that prices overreact to general information and underreact to specific information. Tetlock (2011) discovered that investors might not discern new from stale information and whether other investors have already incorporated it into the asset price. This causes the market to respond excessively to old information too. Both the papers proved how investors' irrationality and low attention can bring to implications contradictory to the EMH, i.e. trading on past and uninformative information.

The positive effect on the aggregated cumulative returns can be explained by the fact that Johnson's commitment to Brexit is reinforced in each of his clear-cut statements. In our case, the reduced uncertainty on Brexit is positively valued by the investors. This supposition is supported by the fact that the market welcomed positively the election of Johnson on 12/12/2019.

5. Conclusion

Investors facing Brexit, an epochal and never seen before event, may lack an adequate set of information which allows to form rationally a single probability distribution of returns. In such a situation of ambiguity investors might consider and price different scenarios, each with its own distribution of returns. In principle, this is not against the semi-strong EMH, as long as the expectations, and in turn securities' fluctuations, are based on public available, new and informative disclosures. However, our study demonstrates that the market overreacted to the unenlightening content posted by the UK Prime Minister on Twitter, an outcome not expected in an EMH world.

Evidence suggests that the statements of the Downing Street's premier trigger positive cumulative abnormal returns. The positive effect on the cumulative abnormal returns can be attributed to investors assigning a positive value to the lower uncertainty on the Brexit process (caused by Johnson's tweet). Results are also confirmed by a robustness check which replicates the methodology on a smaller and less biased subsample, that controls the effects of all sources of information other than Twitter.

Finally, I would like to conclude the paper with some suggestions for future research. The proposed dissertation can be enhanced by analyzing a single or group of stocks instead of the entire FTSE100. It might be interesting to determine the effects of the tweets by sector and see if the results are homogeneous. By a-priori reasoning, we might hypothesize that some securities might have been more damaged by this situation of ambiguity, which has led agents to avoid the sectors most exposed to Brexit.

Furthermore, similar analyses might be extended to other countries or the UK itself using a larger sample (e.g. including Cameron and May's governments).

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Appendices

Keywords
Brexit, negotiation, no-deal, election, Article 50, Great Repeal Bill, Withdrawal Bill, EU, European Union, Euro

Table 1: List of words to classify Brexit's tweets.

Type of Test	20 days	60 days	120 days
White Test	0.024	0.161	0.139
ADF Test	0.036	0.045	0.046
Breusch-Godfrey Test	0.000	0.000	0.000

Table 2: p-values of econometric tests on abnormal returns with different estimation windows (20, 60, 120 days).

White test: H_0: homoscedasticity vs. H_1: no homoscedasticity (heteroscedasticity). ADF Test with constant: H_0: unit root vs. H_1: stationarity. Breusch-Godfrey test: H_0: no 5th order autocorrelation vs. H_1: 5th order autocorrelation.

Date	Event Description
24/07/2019	Boris Johnson formally takes over as Prime Minister.
25/07/2019	Johnson commits to the October date for Brexit and refuses to rule out the possibility of a 'no-deal' Brexit.
01/08/2019	Bank of England announcement on base rate.
19/09/2019	Bank of England announcement on base rate.

03/10/2019	The PM delivers a statement to the Commons, outlining the Government's proposals for a new Brexit deal.
14/10/2019	In front of the Parliament, hew Majesty says that her government's priority is to have Brexit done on 31 October.
17/10/2019	The Prime Minister holds a press conference at the European Council, following the announcement of a new Brexit deal.
19/10/2019	The PM presents his new Brexit deal, but he is defeated. He later writes to Donald Tusk to ask for a Brexit extension.
21/10/2019	The European Union (Withdrawal Agreement) Bill is introduced to Parliament.
22/10/2019	The EU Bill passes its second reading, but the programme motion setting out the timetable is defeated. The PM pauses the legislation.
28/10/2019	EU27 confirmed the Brexit extension to 31 January 2020.
30/10/2019	Ministers approve the European Union (Withdrawal) Act 2018 (Exit Day) (Amendment) (No. 3) Regulations 2019, officially changing the date of “exit day” to 31 January 2020. The government introduces the "Early Parliamentary General Election Bill" which sets the date for a General Election to take place on 12 December.
07/11/2019	Bank of England announcement on base rate.
12/12/2019	General Elections result in Conservative Party majority. Johnson pledges to get Brexit done by 31/01/2020.
19/12/2019	Bank of England announcement on base rate. The Government publishes the EU Bill.
23/01/2019	The EU Bill receives Royal Assent and becomes an Act of Parliament.
30/01/2020	Bank of England announcement on base rate.
31/01/2020	The UK officially left the EU.

Table 3: Dates excluded in the subsample employed for the robustness check.

Cumulative average abnormal returns			
T	**20 days**	**60 days**	**120 days**
Average	2.64%	0.69%	0.50%
t-statistic	9.78	2.88	2.12
p-value	0.000	0.002	0.017

Table 4a: Hypothesis tests on cumulative average abnormal returns (CAARs) by estimation window (T).

		Abnormal returns										
T	**t**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
20 days	Average	0.19%	0.21%	0.24%	0.21%	0.22%	0.24%	0.26%	0.29%	0.29%	0.21%	0.28%
	t-stat	2.32	2.26	2.76	2.56	2.67	2.92	3.75	4.16	3.80	2.82	4.03
	p-value	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
60 days	Average	0.02%	0.04%	0.06%	0.03%	0.04%	0.06%	0.08%	0.11%	0.12%	0.03%	0.10%
	t-stat	0.2	0.39	0.71	0.36	0.50	0.74	1.20	1.62	1.52	0.45	1.53
	p-value	0.42	0.35	0.24	0.36	0.31	0.23	0.12	0.05	0.06	0.33	0.06
120 days	Average	0.00%	0.02%	0.04%	0.01%	0.02%	0.04%	0.07%	0.09%	0.10%	0.02%	0.09%
	t-stat	-0.01	0.21	0.51	0.14	0.29	0.52	0.95	1.37	1.29	0.21	1.28
	p-value	0.50	0.42	0.31	0.44	0.39	0.30	0.17	0.09	0.10	0.42	0.10

Table 4b: Hypothesis tests on abnormal returns (ARs) by estimation window (T).

OLS Regression Model
Dependent variable: CAR_j

	20 days	**60 days**	**120 days**
const	-0.0050 (-0.75)	-0.0119 ** (-2.36)	-0.0135 *** (-2.73)
$log(1 + BJ_j)$	0.0463 *** (4.23)	0.031 *** (3.01)	0.0301 *** (2.96)
CAR_{j-10}	0.1528 * (1.84)	-0.0536 (-0.71)	-0.0158 (-0.20)
$MacroNews_j$	-0.0279 ** (-2.37)	-0.0253 ** (-2.14)	-0.0246 ** (-2.16)
N	135	135	135
r^2	0.3409	0.2372	0.2308
$Adjusted\ r^2$	0.3259	0.2197	0.2132
F(3,131)	7.61	3.84	3.64

Table 5: OLS regression model.

Cumulative average abnormal returns

	20 days	**60 days**	**120 days**
Average	1.77%	1.43%	1.22%
t-statistic	2.96	4.74	4.23
p-value	0.002	0.000	0.000

Table 6a: Robustness check on cumulative average abnormal returns (CAARs) by estimation window.

OLS Regression Model
Dependent variable: CAR_j

	20 days	**60 days**	**120 days**
const	-0.0190 * (-1.95)	-0.0121 * (1.79)	-0.01127 * (-1.93)
$log(1 + BJ_j)$	0.0281 *** (3.14)	0.0171 *** (3.53)	0.0171 *** (3.20)
CAR_{j-10}	-0.2029 (-1.55)	0.1337 (1.13)	0.0060 (0.09)
$MacroNews_j$	-0.0308 ** (-2.27)	-0.0190 * (-1.79)	-0.0168 (1.46)
N	135	135	135
r^2	0.2356	0.2362	0.2478
$Adjusted\ r^2$	0.2181	0.2188	0.2306
F(3,131)	8.63	6.78	4.6

Table 6b: Robustness check on the OLS regression model.